Report No. NAWCADWAR-92022-60

2

AN INVESTIGATION OF SWITCHED RELUCTANCE ROTOR POSITION ESTIMATION USING NEURAL NETWORKS

Jenifer M. Shannon
Air Vehicle and Crew Systems Technology Department (Code 6012)
NAVAL AIR WARFARE CENTER, AIRCRAFT DIVISION
Warminster, PA 18974-5000

FEBRUARY 1992

PROGRESS REPORT
Work Unit Plan No. IRA11
Project ID No. 01B1201

Approved for public release: distribution is unlimited

Prepared for
OFFICE OF SCIENCE & TECHNOLOGY
Naval Air Warfare Center, Aircraft Division
Warminster, PA 18974-5000

NOTICES

REPORT NUMBERING SYSTEM — The numbering of technical project reports issued by the Naval Air Warfare Center, Aircraft Division, Warminster is arranged for specific identification purposes. Each number consists of the Center acronym, the calendar year in which the number was assigned, the sequence number of the report within the specific calendar year, and the official 2-digit correspondence code of the Functional Department responsible for the report. For example: Report No. NAWCADWAR-92001-60 indicates the first Center report for the year 1992 and prepared by the Air Vehicle and Crew Systems Technology Department. The numerical codes are as follows:

CODE	OFFICE OR DEPARTMENT
00	Commanding Officer, NAWCADWAR
01	Technical Director, NAWCADWAR
05	Computer Department
10	AntiSubmarine Warfare Systems Department
20	Tactical Air Systems Department
30	Warfare Systems Analysis Department
50	Mission Avionics Technology Department
60	Air Vehicle & Crew Systems Technology Department
70	Systems & Software Technology Department
80	Engineering Support Group
90	Test & Evaluation Group

PRODUCT ENDORSEMENT — The discussion or instructions concerning commercial products herein do not constitute an endorsement by the Government nor do they convey or imply the license or right to use such products.

Reviewed By: ______________ Branch Head   Date: 4/27/92

Reviewed By: ______________ Division Head   Date: 4/27/92

Reviewed By: ______________ Director/Deputy Director   Date: 29 Apr 92

SECURITY CLASSIFICATION OF THIS PAGE

REPORT DOCUMENTATION PAGE

Form Approved OMB No 0704-0188

1a REPORT SECURITY CLASSIFICATION Unclassified	1b RESTRICTIVE MARKINGS
2a SECURITY CLASSIFICATION AUTHORITY	3 DISTRIBUTION / AVAILABILITY OF REPORT Approved for Public Release; Distribution is Unlimited
2b DECLASSIFICATION / DOWNGRADING SCHEDULE	
4 PERFORMING ORGANIZATION REPORT NUMBER(S) NAWCADWAR-92022-60	5 MONITORING ORGANIZATION REPORT NUMBER(S)
6a NAME OF PERFORMING ORGANIZATION Air Vehicle and Crew Systems Technology Department 6b OFFICE SYMBOL (If applicable) 6012	7a NAME OF MONITORING ORGANIZATION
6c ADDRESS (City, State, and ZIP Code) Naval Air Warfare Center Aircraft Division Warminster, PA 18974-5000	7b ADDRESS (City, State and ZIP Code)
8a NAME OF FUNDING / SPONSORING ORGANIZATION NAVAIRWARCENACDIVWAR 8b OFFICE SYMBOL (If applicable) 01B	9 PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER
8c ADDRESS (City, State, and ZIP Code)	10 SOURCE OF FUNDING NUMBERS PROGRAM ELEMENT NO: PROJECT NO: 01B1201 TASK NO: WORK UNIT ACCESSION NO: IRA11

11 TITLE (Include Security Classification)

An investigation of Switched Reluctance Rotor Position Estimation Using Neural Networks

12 PERSONAL AUTHOR(S)

Jenifer M. Shannon

13a TYPE OF REPORT	13b TIME COVERED	14 DATE OF REPORT (Year, Month, Day)	15 PAGE COUNT
Progress	FROM 10/91 TO 2/92	1992 February	19

16 SUPPLEMENTARY NOTATION

17 COSATI CODES			18 SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
FIELD	GROUP	SUB-GROUP	

19 ABSTRACT (Continue on reverse if necessary and identify by block number)

The Switched Reluctance Machine (SRM) has potential applications in the "More-Electric Aircraft" program. Such applications include fuel and oil pump, actuators, braking systems and integral starter/generators. However, one difficulty in the controller design still exists. Knowledge of the relative position of the rotor with the stator is required for timing of the excitation pulses. This position is conventionally measured by an encoder or resolver. However, for many applications of the SRM such a senosr will not operate in the harsh environment of the machine. Developing a means of estimating the rotor position without the need for a rotor-mounted position sensor is the aim of this research. Specifically, this paper invescigates the possibility of using neural networks for rotor position estimation.

20 DISTRIBUTION / AVAILABILITY OF ABSTRACT ☒ UNCLASSIFIED/UNLIMITED ☐ SAME AS RPT ☐ DTIC USERS	21 ABSTRACT SECURITY CLASSIFICATION UNCLASSIFIED
22a NAME OF RESPONSIBLE INDIVIDUAL Jenifer M. Shannon	22b TELEPHONE (Include Area Code) 215-441-7216 22c OFFICE SYMBOL 6012

DD Form 1473, JUN 86 Previous editions are obsolete SECURITY CLASSIFICATION OF THIS PAGE

S/N 0102-LF-014-6603

CONTENTS

FIGURES

INTRODUCTION

The switched reluctance machine (SRM) is being incorporated into the designs of new electric actuator motors and integral starter/generators due to its inherent robustness and fault tolerant qualities. The SRM rotor is more robust than conventional machines since it has no windings or magnets which limit the integrity of the rotor structure. The stator windings are also different from a conventional stator in that they are completely independent from each other providing electrical isolation. If a phase winding is subjected to a short circuit, the phase is simply de-excited allowing the machine to continue operation on the remaining phases; thus, the short is not propagated to other windings and power is not cut off as in conventional machines.

The SRM torque is developed due to the magnetic attraction between the rotor and stator poles. The timing of the magnetic excitation with respect to the relative position of the rotor poles to the stator poles controls the amplitude and polarity of the torque pulses. A SRM can be operated as either a motor or a generator depending on the the timing of the excitation. If the machine is excited as a rotor pole is approaching a stator pole, the slope of the torque is positive and the machine will behave as a motor. On the other hand, if the machine is excited as a rotor pole is passing by a stator pole, the slope of the torque is negative and the machine will behave as a generator. Given the capability of a single machine being operated as both a motor and a generator, the SRM lends itself as a strong candidate for a starter/generator.

In order to obtain the correct timing for the machine's excitation, knowledge of the relative position between the rotor and the stator is required. The present method of determining this relative angle utilizes a rotor-mounted resolver or absolute encoder. This method can provide precise angles, but it represents a single point of failure to the system. This technique also limits the system's ability to operate in high temperature environments for which the switched reluctance machine is otherwise well suited.

Due to the limiting factors of the encoder/resolver technique, alternative methods of determining rotor position are being pursued. The stator flux linkages can be estimated by integrating measured voltages and currents. The excitation (the magnetomotive force) for each phase is proportional to the measured current and the number of turns per pole on the stator. These flux linkages and excitations can then be incorporated into a magnetic circuit model from which the relative rotor angle can be determined through mathematical techniques involving finite element analysis and the Newton Raphson method [1]. There are a number of disadvantages associated with this method. The extensive computation to be performed for each discrete input results in a costly delay. In other words, a real time angle is not available, so the maximum speed of rotation and the number of phases of the machine are limited. By limiting the speed, the machine's performance is hindered, and by limiting the number of phases, the fault tolerance of the machine is limited.

The objective of this research is to develop an artificial neural network that will estimate the rotor position and eliminate the need for the shaft position sensor. Existing sensors provide phase voltages and currents to the SRM controller. The network will use these measured voltages and currents as inputs, process them, and output the rotor/stator angle for controlling the excitation. The network will be a heteroassociative nonlinear mapping network providing the least computational, most responsive, and highest fault tolerant solution.

There are a number of reasons that a neural network was chosen as an approach to solving the stated problem. The main advantage of using an artificial neural network as opposed to another computational technique for rotor location identification is that the network produces an immediate response with minimal computation for a given input set, whereas mathematical techniques involving complex modeling and finite element analysis require extensive computation for each input measurement. An angle that is available in real time enables the design of a high performance, highly fault tolerant machine. Another advantage of using neural networks is their documented ability to provide correct outputs given faulty or missing sensor inputs. Thus, a neural network would provide an additional layer of fault tolerance to the system. In addition, the voltage and current measurements to be used as inputs are generally noisy. Neural networks are well known for their ability to generalize and thus successfully deal with a certain amount of noise.

METHODS

The training/testing data was obtained from a 120 hp 6/4 pole switched reluctance machine. The geometry of the machine and the relative angle, θ, are shown in Figure 1. The windings of opposite poles are connected in series to make up a single phase. The other ends of the windings are connected to the converter circuit. Only one phase connection is shown in Figure 1 for simplicity.

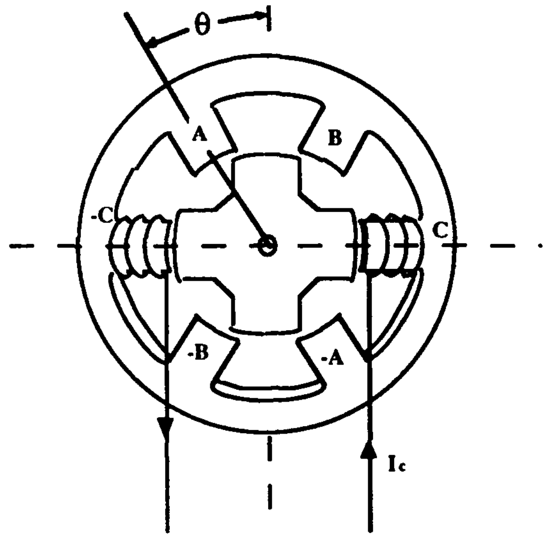
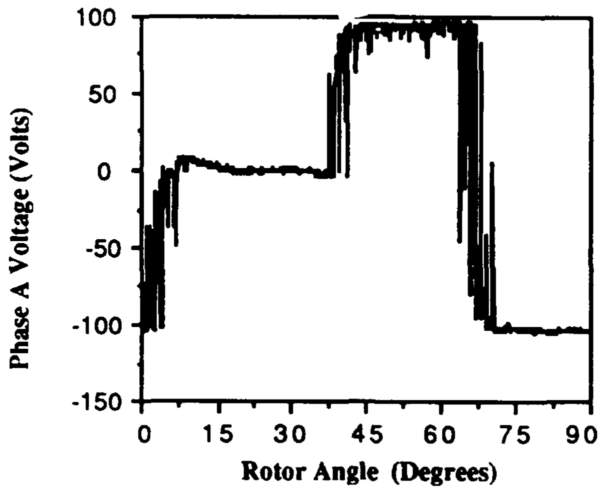
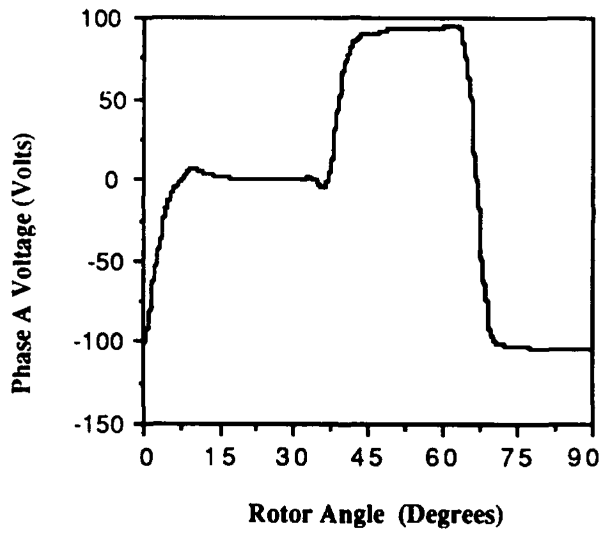


Figure 1. Geometry of the SRM

The data used for training the networks was obtained using a data acquisition system with a 25 KHz sampling rate and a 16 bit resolution. Parameters measured included three phase voltages, three phase currents, the rotational speed and the relative rotor angle. The voltages and currents are used as the six inputs to the neural network and the rotor angle is the desired output. Some manipulation of the data was necessary due to an excessive amount of noise present. The data was provided in the order that it was measured. Each file contained a large number of revolutions under varying speed and load conditions. Each file was rearranged in order of increasing rotor angle. Then a single electrical period, 90 mechanical degrees, was extracted. This data was then put through a low pass filter to extinguish the high frequency noise. Examples of current and voltage waveforms before and after filtering are shown in Figure 2.



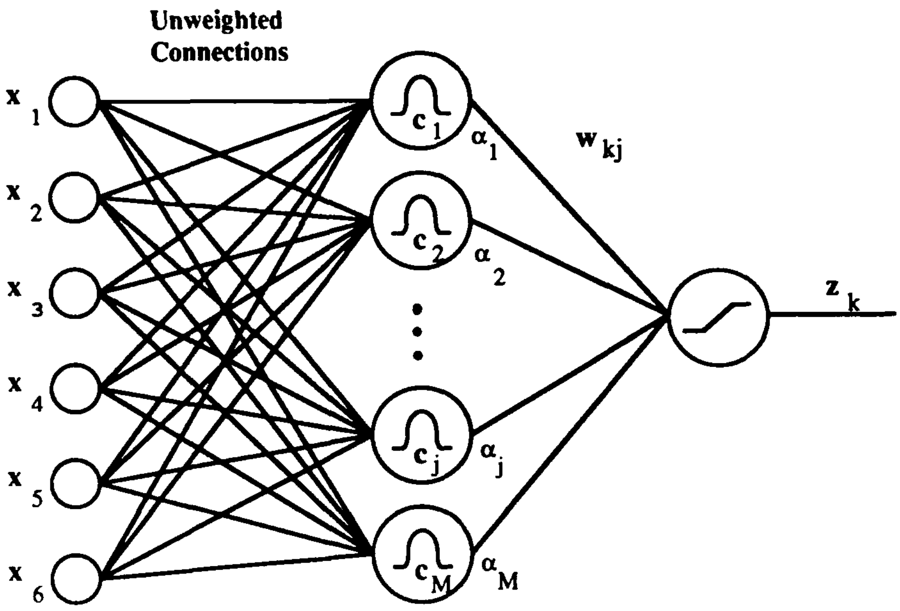
(a) Unfiltered Voltage Waveform



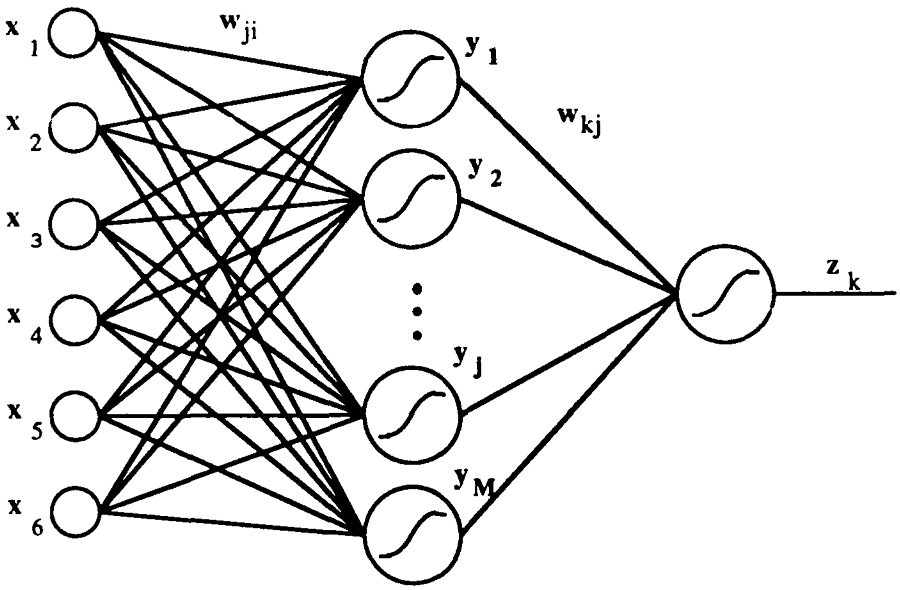
(b) Filtered Voltage Waveform

Figure 2. Measured Waveforms / Pre and Post Filtering

Two types of network architectures were investigated for this application, a backpropagation network and a Radial Basis Function (RBF) network. Each architecture is shown in Figure 3.



(a) Radial Basis Function Network Architecture



(b) Backpropagation Network Architecture

Figure 3. Basic Architectures

A standard backpropagation learning paradigm was utilized. The transfer function chosen for the hidden layer was the sigmoid function. The output of a hidden unit can be described as

$$y_j = f(\Sigma w_{ji} * x_i)$$

where w_{ji} is the weight associated with the connection from the *ith* input to the *jth* hidden unit, x_i is the input value for the *ith* input, and $f(z)$ is the sigmoid function,

$$f(z) = 1 / (1 + e^{-z}) .$$

The output layer also utilized a sigmoid function. Both three and four layer architectures were investigated. The normalized cumulative delta rule was chosen for the learning rule. The error, e_j , is computed as the difference between the desired or measured rotor angle and the computed angle. The weights are updated by the following equation:

$$\Delta w'_{ji} = \text{lcoef} * e_j * x_i + \text{momentum} * \Delta w_{ji}$$

where lcoef is the learning coefficient and Δwji is the previous weight update for the connection between the *ith* input and the *jth* hidden unit.

A major effort of this research involved exploring the Radial Basis Function (RBF) network [2],[3]. A RBF network is a three layer network. The first layer serves as an input layer, the middle or hidden layer uses the radial basis functions as neurons, and the output layer uses simple summation neurons. The nonlinear transfer function used in the hidden layer can be chosen from a few typical functions including the thin-plate-spline function, the multiquadric function and the Gaussian function. The most common choice and the function employed here is the Gaussian. The activation or the output of the *jth* hidden unit is calculated as follows:

$$\alpha_{ji} = \exp(-\| c_j - x_i \|^2 / \sigma^2)$$

where x_i is the input value, c_j is the center of the *j*th radial unit in input space, and σ is the width of the radial unit or the size of the unit in input space.

The radial basis function is also known as the hyperspherical decision function because the feature space of the network is divided into M hyperspherical decision regions where M is the number of hidden neurons. The traditional implementation of this network requires as many hidden neurons as training points. Since each electrical period consists of over 1000 input vectors, this implementation would be impractical. The number of neurons must be reduced for a successful implementation. The trick is in selecting the RBF centers. Initially, the centers were chosen randomly from the input space. Many centers were required using this technique since the training data did not uniformly cover the input space. Some difficulties were encountered using this method of choosing centers. Limited success was obtained using very small networks. As the network size was increased, the use of linear regression in solving for the weights became more impractical and the algorithm failed due to numerical ill-conditioning. In an attempt to avoid this situation, a singular value decomposition (SVD) technique was tried. The number of neurons was able to be increased somewhat; however, a limit was also reached at which the solution would not converge. Even if a network with a larger number of hidden neurons was obtainable, the method of randomly choosing the Gaussian centers is lacking repeatability and will result in an inefficient network. (Inefficient meaning poor performance with a large number of neurons.)

For these reasons an alternate method of choosing centers was investigated. The orthogonal least squares (OLS) method can be used to choose a set of centers from a large set of candidates [4]. In this technique's implementation, a matrix of size N x M is manipulated where N is the number of training points and M is the number of candidate centers. If N = M, the size of this matrix is extremely large and computer memory becomes a problem. Therefore, some technique of reducing the number of candidate centers was required. Experimentation with the ratio of the final number of centers to the number of candidate centers was performed. For example, if every 5th data point out of 1000 points is chosen as a candidate center and 100 neurons is chosen as the final number of neurons the resultant ratio is 0.5.

Once the center vectors are chosen, the size of each RBF needs to be determined. The size of each RBF is chosen so any point in the input space would be within the field of at least two neurons. This should enable a smooth fit of the desired network outputs.

Since the only weighted connections are those from the RBFs to the output which is a simple summation, training can be performed by linear regression. The regression correlates the desired network outputs with the hidden node activations.

RESULTS & DISCUSSION

The performance of the networks is determined by two methods. First the network is tested with the data which was used for training in order to provide an indication if the chosen architecture showed any signs of promise. Second, the network is tested with the noisy input data or filtered data not previously used for training in order to assess the network's ability to generalize and operate in a more realistic environment.

Figure 4. shows the outcome of the first attempt at using the RBF network. The graph's x-axis, the step number, represents the record number of the training file. There were 1014 training vectors used in this case. The y-axis represents the rotor angle. The network was trained over 90°, which corresponds to 360 electrical degrees for this particular machine. The test data was presented to the network in ascending order; thus, the desired output is a straight line with a positive slope. The network's actual output is overlaid upon the desired output. As can be observed in Figure 4., the network had some success in mapping the correct output, but its mapping is too noisy for any practical implementation.

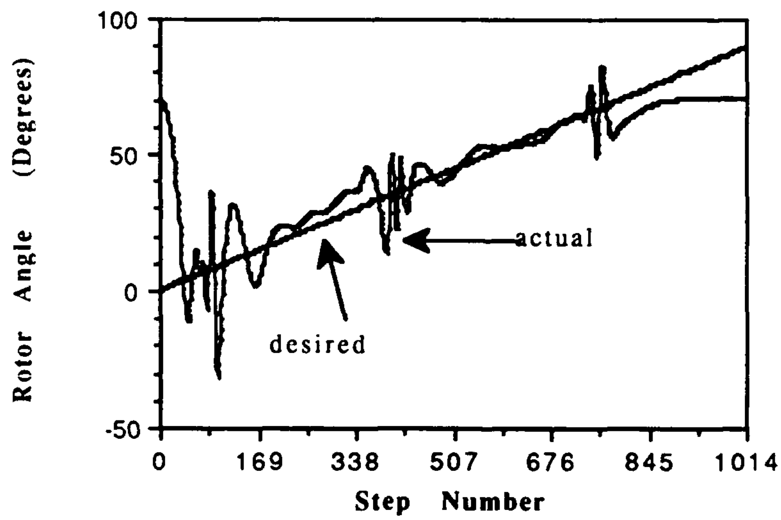


Figure 4. 6:20:1 RBF Network

(Weights solved by linear regression)

The development of this network involved using linear regression to solve for the weights. Linear regression is a highly desirable technique to use because its implementation is straightforward and it finds the solution in only a single pass; in other words, iterative training is unnecessary. Twenty is the maximum number of hidden neurons that could be used before the linear regression matrix became singular. A network of only twenty neurons is not capable of mapping a six dimensional function; therefore, an alternate method of solving for the weights was examined.

Figure 5. shows the output from a RBF using singular value decomposition to solve for the weights. A canned SVD routine from the application, MATLAB, was used. When the number of neurons was greater than 100, the SVD routine could not converge. So, even though the number of neurons using SVD was greater than the number of neurons using linear regression, this network's performance was still unacceptable.

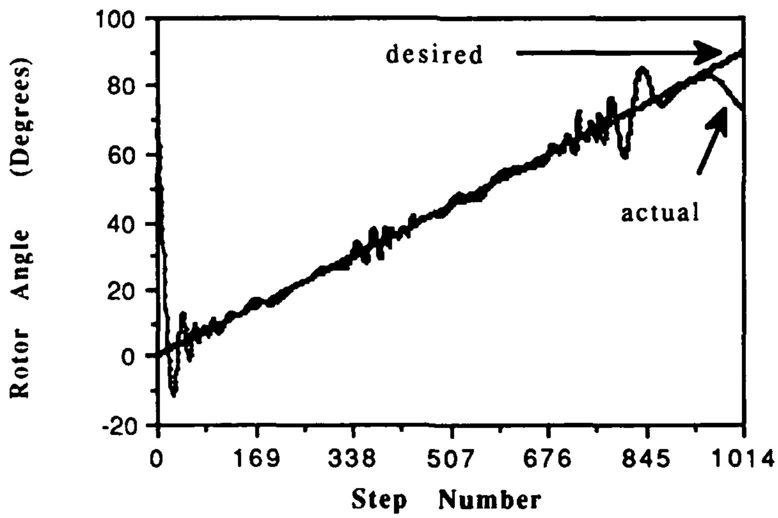


Figure 5. 6:100:1 RBF Network (Weight solved by SVD)

The reason that the linear regression matrix becomes singular and the SVD algorithm does not converge is probably because the centers of the Gaussians which are randomly chosen are not representative of the input space. Based on this assumption, the orthogonal least squares method of choosing centers was investigated. The orthogonal least squares method was difficult to implement. The method of choosing the original candidate centers is unclear. Initial attempts to utilize OLS were unsuccessful and further effort is required.

Figure 6. shows the results from the first attempt at using the backpropagation network. At this point, the method of choosing the training points for the networks was re-evaluated. It was determined that preceding input vectors should be fed into the network in addition to the real time information. Since this method would greatly increase the number of inputs to the network, the resolution of the training data was reduced by a factor of ten. Up to seven previous steps of training vectors were fed into the network. The results of training in this manner with 95 hidden neurons are shown in Figure 7.

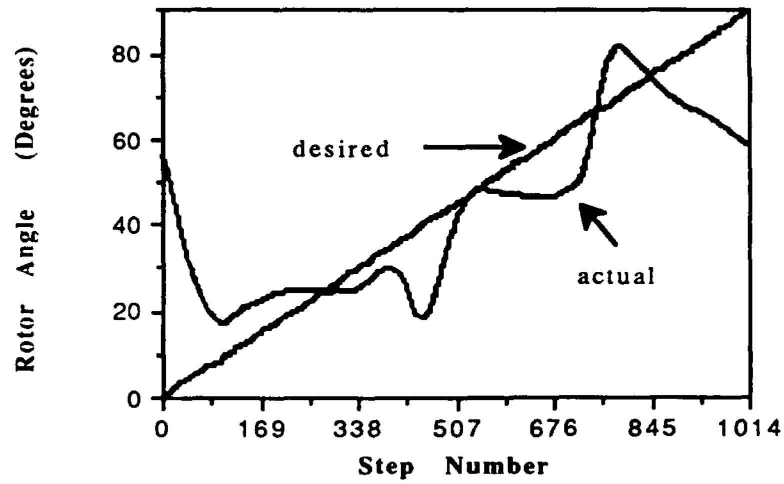


Figure 6. 6:40:1 Backpropagation Network

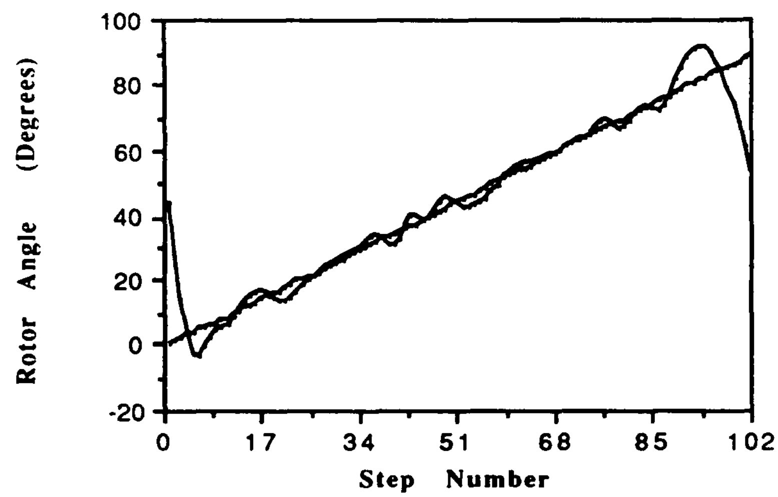


Figure 7. 48:95:1 Backpropagation Network

Note the transient-like deviations at the edges of the performance plots. This problem, which shall be termed edge transients, has been present in every network architecture using every different training technique to date. Its cause is unclear, however a number of hypotheses have been formed.

At first it appeared that the edge transients were due to a non-uniqueness in the input data. This hypothesis, however, was disproven by the following tests. The training data was shifted by 20°, and the transients still remained at the beginning and end of the testing data, even though this data included different vectors from the unshifted data. Also, the entire training set's output space was reduced to cover only 60 mechanical degrees, yet the transients still appeared at the beginning and end of the 60°. From these tests, it has been determined that the edge transients are independent of the training vectors.

A second theory was investigated. In the backpropagation networks, the output neuron employs a sigmoid transfer function which is nonlinear at its edges. The theory proposes that the mapping into this nonlinear region caused the edge transients. Two attempts to validate this proposal were made. First, the output space of the network was expanded from 0 to 90° to -20 to 110°. The expansion was performed by changing the maximum and minimum numbers used for normalization. The intent of this expansion was to map the desired outputs of 0 to 90° on the more linear section of the sigmoid function. The results of this attempt are shown in Figure 8.

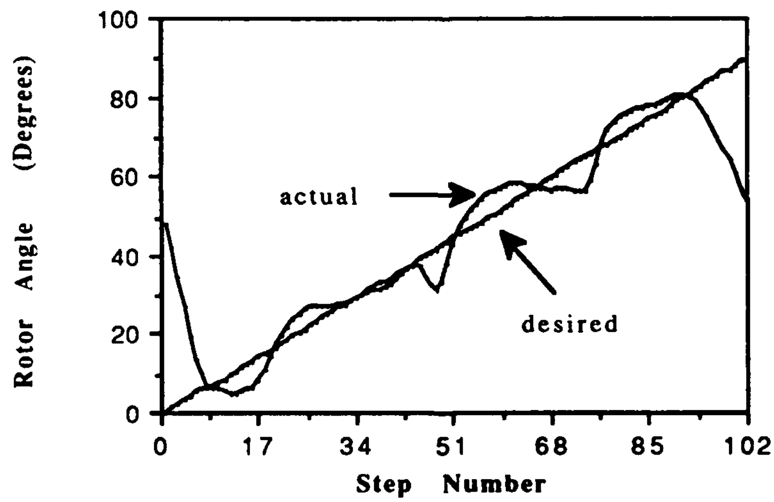


Figure 8. 48:95:1 Backpropagation Network Trained with Expanded Output Space

The second attempt involved making the output neuron completely linear. Training in this manner was much more sensitive. The learning coefficient and momentum had to be kept very small (lcoef = 0.005, momentum = 0.01) or otherwise the weights would quickly become large and negative or large and positive. Training was tedious and time consuming. The results are shown in Figure 9. As can be seen by the Figures, evidence to prove this theory is lacking.

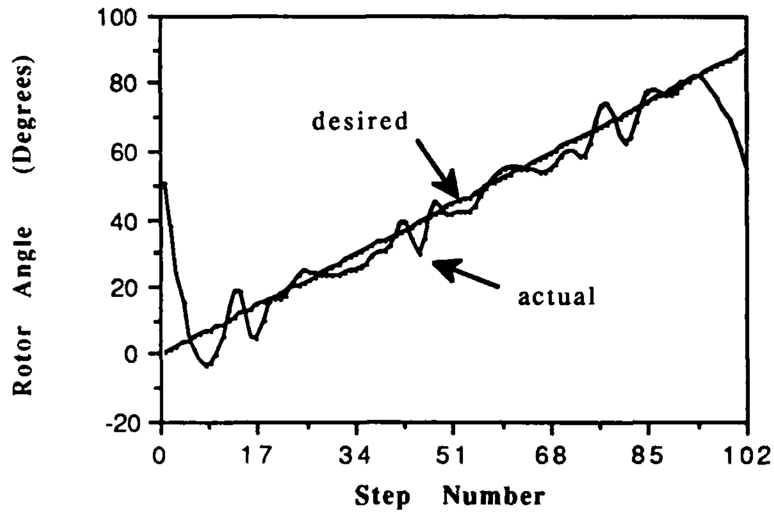


Figure 9. 48:95:1 Backpropagation Network with Linear Output

A third theory explaining the cause of the edge transients has been developed but has not yet been fully validated. The desired output signal is not just a single straight line from 0 to 90°, but a continuous periodic sawtooth waveform. As one rotor pole completes its electrical period with the stator pole, the next rotor pole begins a new electrical period. The networks have been trained to expect an angle close to 0° following an angle of 90°. This makes the output have a sharp transition at the wrap around point. The theory proposes that this transition is too abrupt for the network to recognize. To validate this theory, a training file was created in which the 0° point was moved to the end of the file so that the sawtooth waveform is more evident. The behavior of a network trained with this file is shown in Figure 10. Notice that the transient only appears at the wrap around point at the end of the file and not at the beginning.

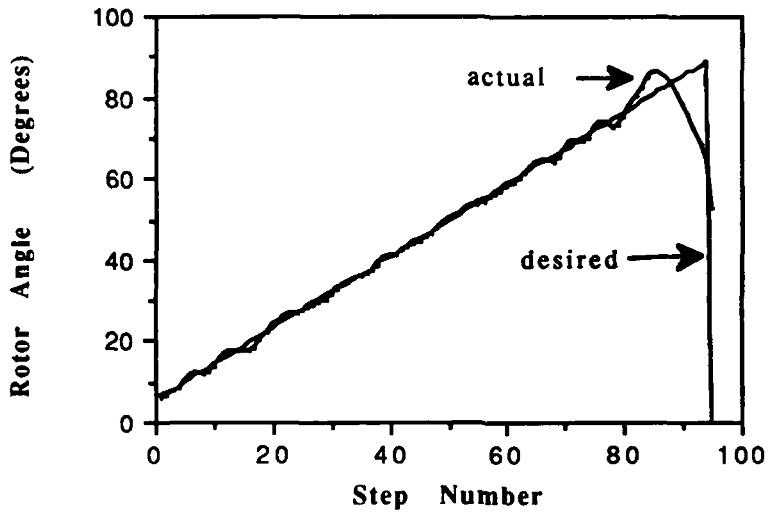


Figure 10. 48:95:1 Backpropagation Network Trained with Reordered Data

Although this explanation has credence, the best solution for the problem in not obvious. A number of options for solving the problem can be tried. The resolution of the training data can be increased at the wrap around point; or the error function can be made quadratic or cubic in order to emphasize the large errors more so than the smaller errors, since the large errors are due to the edge transients.

If these options are unsuccessful, a more complex method of solving the problem may be required. A multi-network with a modular architecture that will allow task decomposition is another possible solution [5]. The network would be composed of three sub-networks. Network #1 would place the wrap around point near 90°, at the end of the output space, as was done in the network in Figure 10. Network #2 would place the wrap around point near 0°, at the beginning of the output space. Network #3 would perform a gating function; it would choose between Network #1 and #2's outputs. If the output space is less than 45°, then Network #3 would choose Network #1's output since there would be no edge transient in this output region. Similarly, if the output space is greater than 45°, Network #3 would choose Network #2's output since there would be no edge transient in this output region.

CONCLUSIONS

The efforts of this research have shown that the application of neural networks to SRM rotor position estimation is feasible. The optimal network architecture has not yet been identified, but two types of paradigms have been investigated, the RBF network and the backpropagation network.

Although the backpropagation networks' performance was comparable to that of the RBF networks, it is anticipated that as the training input space is increased by adding new waveforms to the training data, backpropagation performance will not fare as well as RBF performance. This projection is based upon the nature of the waveforms. The amplitude and overall shape of the waveform will change due to different loading conditions under which the SRM must operate. Since the backpropagation network normalizes the input data, some difficulty in generalizing new waveforms is anticipated.

A distinctive performance problem, edge transients, has been discovered in both the RBF networks and the backpropagation networks. A number of theories as to the source of this problem have been developed and investigated. The strongest theory identifies the wrap around point from the end of the electrical period to the beginning of the next period as a sharp transition point which is difficult to map precisely. Potential solutions have been proposed. The most promising solution involves the creation of a modular network that would decompose the output space in such a manner that the edge transient regions could be avoided.

FURTHER INVESTIGATION

Before exploring alternate training methods and network architectures, the edge transient problem must be solved. The possible solutions described in the Results and Discussion section should be attempted.

Additional attempts at using the RBF functions using previous information (more inputs) as was done in the backpropagation network, should result in a better performing RBF network. Alternate techniques for choosing candidate RBF centers should be investigated. Further observation of the effect of varying the size of the RBFs (width of the Gaussians) is also recommended.

The optimum resolution of the training data and the best number of previous vectors to be fed as inputs should be determined. Also, even though three phase voltages and currents are available as inputs, they are not all required to make the input space vector unique for each output point. All voltages and currents should be used, but the network should be tested with missing inputs to evaluate its level of redundancy.

Additional investigation into alternate network architectures and training schemes is suggested. A determination of the effect of training with additional waveforms is required before a decision as to which type of network (RBF or backpropagation) is more suitable for this application.

ACKNOWLEDGEMENTS

The measured machine data was provided by Dr. James P. Lyons of GE Corporate Research and Development.

REFERENCES

[1] Preston M., Lyons J., "A Switched Reluctance Motor Model with Mutual Coupling and Multi-Phase Excitation", IEEE Transactions on Magnetics, Vol. 27, Issue 6, Nov. 1991.

[2] Cios K.J., Tjia R.E., Liu N., Langenderfer R.A., "Study of Continuous ID3 and Radial Basis Function Algorithms for the Recognition of Glass Defects", IJCNN Conference, Vol. 1, July, 1991.

[3] Leonard J.A., Kramer M.A., "Radial Basis Function Networks for Classifying Process Faults", IEEE Control Systems, April 1991.

[4] Chen S., Cowan F.N., Grant P.M., "Orthogonal Least Squares Learning Algorithm for Radial Basis Function Networks", IEEE Trans. on Neural Networks, Vol. 2., No. 2, March 1991.

[5] Jacobs R.A., Jordan M.I., "A Modular Connectionist Architecture For Learning Piecewise Control Strategies", Proceedings of the 1991 American Control Conference, Vol. 2., pp. 1597-1602.